Nudging and Subsidizing for the Adoption of Smart Meters: A Choice Experiment with French Farmers*

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Abstract

In a context of water scarcity, optimizing its use in the agricultural sector is one of the spearheads of current agricultural policies. In this paper, we test several instruments to encourage the voluntary adoption of water smart meters by farmers. Using a choice experiment with randomized treatments on 1,272 French farmers, we consider a conditional subsidy modeled on the collective bonus proposed by Kuhfuss et al. (2016) and two types of nudges (priming and framing vs testimony). The conditional subsidy offered is a certain amount of money given to each farmer who adopts a smart meter provided that enough other farmers adopt the new technology as well. We analyze the impact of two parameters for this policy instrument: the amount of the subsidy offered and the level of the conditional threshold that is chosen. Our results uniquely show that the higher the threshold, the more farmers identify the adoption of smart meters as the social norm they wish to follow. Moreover, the conditional subsidy and nudges are complement; when combined with a high amount of subsidy and a high adoption threshold, nudges perform better in the sense that farmers choose less often the status quo option.

Keywords : *Choice experiment, Randomized experiment, Smart water meters, French farmers, Social norms, Nudges.*

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1 Introduction

Agricultural sector is the leading consumer of water for crop irrigation: 70% at the world wide scale. In August 2019, the World Resources Institute emphasized that during the last decades, the water stress and the number of water restrictions have globally increased during the summer, therefore impacting economic activity, and farmers activity in particular.[1] In this context, one of the main concerns, defined by the European Union in the Water Framework Directive (WFD), is to optimize the water management and consumption in the agricultural sector. To deal with this issue, several policies or economic instruments can be used. A first option is to set a high price for water to encourage farmers to limit their water consumption. Such a solution may be politically difficult to implement, in particular in the French context where farmers are already showing some disappointment with respect to the different measures implemented at the European level. Moreover, even if an increase in water price would reduce its demand, the empirical literature already shows that, in practice, the price of water is too low to be seen as a significant cost of production for farmers activity (Gómez-Limón and Riesgo, 2004a,b). On the supply side, a second option is to implement more efficient water tool management as, for example, water inter-basin transfer or treated wastewater (Alcon et al., 2014). However, even if these policy strategies are well accepted by farmers, they take time to be implemented and are expensive.

A third alternative is the adoption of more efficient *farmer water use management* (e.g. drip technology, deficit irrigation, water-use rights) and *new technologies* (smart water meters). While the first have already been studied (Alcon et al., 2014; Skaggs, 2001; Saleth and Dinar, 2000), evidence from the literature on the use of smart water meters in the agricultural sector remains limited. Some exceptions include Wang et al. (2017) for China, Zekri et al. (2017) for Oman and Chabé-Ferret et al. (2019) for France. Although Zekri et al. (2017) show that adopting smart water meters may result in significant gains in terms of groundwater management, Chabé-Ferret et al. (2019) conclude that using smart meters for inducing changes in irrigation decision of farmers remains challenging.

In this paper, we first assess the French farmer's willingness-to-pay (WTP) for different characteristics of water smart meters. We then test different incentive instruments to encourage voluntary adoption of water smart meters by farmers. As a result, we uniquely

[1]See https://www.wri.org/applications/aqueduct/country-rankings/.

provide evidence that the use of smart water meters by farmers, and therefore the gains in terms of groundwater management, is conditioned on the policy design adopted to promote and encourage the adoption of such technology.

Smart meters may allow a better management of water resources by managers and farmers for different reasons. It offers farmers a continuous remote consumption, a possibility to track their individual consumption and an online access to various information relating to water management (Chabé-Ferret et al., 2019). In addition, by allowing precise and quasi real-time measurement of the withdrawn flows, managers can understand and anticipate water resource needs (Monks et al., 2019). This significantly improves the irrigation and water uses for local water managers (better management of the water releases, decrease of the useless withdrawals and decrease of the frequency of the restrictions). Smart meters therefore can be seen as public goods. Public authorities may decide to reward the adoption of smart meters by farmers by subsidizing them. However, to be effective in improving water management at the territory level, this innovation must be accompanied by a massive voluntary adoption of smart meters by farmers: the greater the number of irrigating farmers who have adopted a smart meter on the same watershed, the better the management of the resource, which reduces the risk of shortage and prohibition of irrigating for all farmers. This requires that a certain threshold of adoption rate by farmers in a territory is reached before the technology is implemented.

At the same time, smart meters are generally more expensive than mechanical ones, in particular because of the technology they incorporate. In addition, mechanical meters record on average 15-20% less than real water consumption. Therefore, for the same consumption, the water bill might be higher on average with a smart meter since the measurement of the discharged flows is more precise than with mechanical meters (which under-estimate water consumption). Moreover, smart meters generate detailed data. The almost continuous automatic surveys allow for the creation of farmers' consumption profiles and, therefore, a better control of their irrigation. This consumption profile represents information that can be costly for farmers in the long term (*i.e.*, increase in water bill, modified and discriminated pricing policy depending on farmers' profile) and can generate free riding behaviors. Those who keep their mechanical meter will continue to have a underestimated consumption and will benefit from the improvement of water management accompanied by reduction of restrictions due to smart meters development but without participating.[2]

Given this trade-off, it is crucial to study and understand what the most appropriate public policy design is to maximize the voluntary adoption rate of smart meters.

The monetary incentive that we consider is a conditional subsidy. This subsidy is modeled on the collective bonus proposed by Kuhfuss et al. (2016) in their hypothetical agri-environmental schemes (AES) in which the monetary bonus is paid to enrolled farmers, in addition to the usual AES payment, only if the aggregate enrolled farming land in the territory reaches 50%. Here, the subsidy offered is a certain amount of money given to each farmer who adopts a smart meter provided that enough other farmers adopt the new technology as well. Two parameters of this policy instrument are tested: the amount of the subsidy and the level of the conditional threshold (*i.e.*, the rate of the smart meter adoption).

As a complement to the traditional incentives-based instrument, non-monetary incentives are used to be implemented to reinforce their impact (Lehner et al., 2016; Schubert, 2017). In this experiment, we test the use of nudges to increase incentives for farmers to adopt smart meters. Nudges are simple, costless and non-coercive actions (use of default options, framing, priming, social norms, etc.). Their aim is to provide incentives for economic agents to act in a given direction. Particularly encouraging results using nudges with respect to environmental conservation have been observed in the literature (Allcott, 2011; Costa and Kahn, 2013; Ferraro and Price, 2013; Egebark and Ekström, 2016). Our decision to consider nudges in addition to monetary incentives is also motivated by recent evidence (Myers and Souza, 2020) highlighting that, in a context of energy conservation, some nudges (competitiveness, moral suasion or social norms) are inefficient when monetary incentives are not at stake as, for instance, when targeted agents do not pay energy bills (college residence for example).

We use a choice experiment (CE) with treatments (see LaRiviere et al. (2014) for another example) to assess French farmers' preferences for the adoption of smart water meters. In our survey, we propose a conditional subsidy with different amounts and we vary the thresholds of the conditional subsidy in the treatments. We also study two types of nudges: priming and framing (first nudge) and testimony (second nudge). We finally

[2] At the same time, measurement errors benefits some and not others. Thus, the development of smart meters also allows better equity unlike mechanical meters. Besides, smart meters induce private benefit related to the alert message sending in the case of abnormal consumption as water leaks. These elements reduce the free riding benefits.

compute the farmers' WTP/WTA for smart water meters.

Our contribution is twofold. First, to our knowledge, this is the first CE conducted at the national scale with more than a thousand farmers' responses. This allows us to conclude more generally on the effects of incentive policies and their application to other case studies. Second, based on an experiment testing simultaneously monetary and nudge incentives, we provide guidelines for policies related to water management in agriculture. Our results uniquely show that the respondents are not discouraged by a very high threshold of 75%. On the contrary, the higher the announced threshold, the more farmers identify the adoption of smart meters as the social norm they wish to follow. In addition, nudges appear to be generally effective and, in particular, when a testimony is associated to a high threshold conditional subsidy.

The remaining of this article is organized as follow. We present the literature related to the conditional subsidy and nudges in Section 2. Section 3 details the choice experiment with the experimental design and the choice modelling. Data is described in Section 4. We spell out the results in Section 5, and a discussion concludes our paper in Section 6.

2 Incentive instruments for smart meters' adoption

In this section we first detail the conditional subsidy we consider in this study and then turn to green nudges.

2.1 Conditional subsidy to encourage collective adoption

By lowering the cost for farmers, a subsidy seems an interesting financial instrument to encourage the adoption of smart meters. In addition, monetary incentives such as subsidies signal the importance society places on smart meters. Indeed, social norms can have a significant impact in the diffusion of new technologies, especially when the new technology requires mass adoption to be socially relevant.

Following Schwartz (1977), social norms correspond to expectations on behaviors that one should adopt in specific contexts. More recently, Fehr and Schurtenberger (2018) have defined social norms as "standards of behaviors". Eymess and Florian (2019) also rely on this notion of expectations, but precise it. Social norms are not only expectations about the behavior that should be adopted, but also expectations about what other individuals actually do. Obviously, social norms appear to be rules that guide individual behaviors in given situation, and these rules are influenced by own perception about what other individuals do. When individuals prefer to act like most others, beliefs can be self-fulfilling, and altered expectations about what others will do can lead to rapid behavioral changes (Young, 2015). Thus, as claimed by Nyborg et al. (2016), a potentially powerful role of policy is to provide reasons for individuals to change their expectations.

There is a theoretical literature considering behavioural models which show that government subsidies can increase private contributions to a public good (Andreoni and Bergstrom, 1996; Rege, 2004). More precisely, applying evolutionary game theory, Rege (2004) shows that when agents have preferences for social approval, government subsidies can crowd in social norms for voluntary contributions to a public good. A policy that changes monetary incentives tells farmers that the incentives for others to adopt smart meters are changed, not just their own, making it reasonable to change their beliefs about the rate of smart meter adoption. Even if expectations and beliefs are difficult to steer, it is in this perspective that we propose to analyse the impact of a conditional subsidy. Our objective is to impact farmers' perception about the "right" behavior (to adopt the smart meter in our case) and to change farmers' beliefs about the rate of smart meter adoption.

The conditional subsidy considered follows the same logic as the conditional bonus tested by Kuhfuss et al. (2016) in a choice experiment for AES on French winegrowers. The conditional bonus is paid to each farmer who has signed a herbicides reduction contract, in addition to the contract payment, provided that 50% of farming land in the area of interest is enrolled in the AES. The main objective was to introduce a collective dimension in individual agri-environmental contracts to induce a collective behavioural change dynamic. Kuhfuss et al. (2016) have shown that this conditional bonus can be a powerful incentive tool to increase farmers' participation rate without increasing public expenditure. Indeed, the average WTA to enrol in a AES which offers a conditional bonus is reduced by an amount which is greater than the expected bonus payment. The incentive payment we consider here is not a bonus which adds to a payment, but a subsidy which lowers the cost of a smart meter. In addition, Kuhfuss et al. (2016) define the threshold in terms of enrolled acreage, while in the present study we consider the threshold as the rate of farmers' participation. Otherwise, our conditional subsidy follows the same idea. It is an amount of money which is given to every farmer who bought a smart meter, if a predefined rate of adoption is reached in the sector.

Usually, the announced threshold is 50% as we consider that social norms are driven by the majority. However, theoretical models of critical mass have shown how minority groups can initiate social change dynamics in the emergence of new social conventions and the existence of tipping points has been empirically demonstrated (Centola et al., 2018). Still, there is insufficient insight on the coevolution of social norms and different policy instruments (Kinzig et al., 2013). In this paper we modestly attempt to test different thresholds on the effectiveness of a conditional subsidy. It is not clear in the case of smart meters what is the minimum rate of adoption to make the smart meter really effective. Therefore, we take advantage of this context to test different conditional thresholds to assess whether farmers are sensitive to them.

2.2 Green nudges

Since the last decade, there has been a growing literature regarding the potential of nudges to steer pro-environmental behaviors (Schubert, 2017).

In environmental economics and psychology, most studies on green nudges focused on assessing the effects of social norms and default options to reduce natural resource consumption or energy consumption. Concerning electricity consumption, several studies reported encouraging results following the use of social norm and social comparison (Schultz et al., 2007; Goldstein et al., 2008; Allcott, 2011; Costa and Kahn, 2013), with reductions of electricity consumption of around 2%. Studies on the use of social norms to reduce water consumption (Ferraro and Price, 2013; Brent et al., 2016) reported reductions of water consumption of around 5%. Therefore, nudges based on social norm can be a cost-effective tool to modify the behavior of a large proportion of consumers' at a small cost (Chabé-Ferret et al., 2019). In addition to the studies on the effects of social norms, other studies have focused on the efficiency of default options to improve environmental quality with mixed results (Löfgren et al., 2012; Egebark and Ekström, 2016; Ghesla et al., 2019).

Our objective with the nudge incentives is to induce farmers to adopt a smart water meter. As previously explained, in the literature in environmental economics, most studies focused on the use of social norms or default options. In our case, we cannot consider these two possibilities. Smart meters represent a new technology and, therefore, less than 5% of farmers already have a smart meter: their adoption is not the norm yet among farmers. Moreover, the adoption of smart meters is not a default that can be proposed to farmers. Therefore, we had to consider other types of leviers.

A first possibility is to rely on agents' involvement to push them to adopt smart water meters, *i.e.*, to make agents active. In that case, nudges may take the form of information provision beforehand the decision-making (before the choice experiment) using *reminders* (Thaler and Sunstein, 2008), regarding the scarcity of water resources and its consequences in our case. Alternatively, we can also consider *priming*, that it to say a stimulus (Bargh and Gollwitzer, 1994; Bargh et al., 2001) to raise awareness on the necessity to adopt smart water meters (through a question regarding the importance of water management for instance). Priming has been shown to induce encouraging results in the literature (Bargh, 2006; Friis et al., 2017; Bimonte et al., 2020). A third approach is to involve agents through *commitment*. Empirical evidence have shown that asking individuals to commit may be an effective way to change their behavior (Ariely and Wertenbroch, 2002; Baca-Motes et al., 2012; Dolan et al., 2012) and especially to foster pro-environmental behaviour. Werner et al. (1995) showed that individuals who wrote environmental commitment are more likely to participate in a curbside recycling program.

A second possibility is to provide information on the others (agents are more inactive in that second case). Indeed, as previously discussed, we cannot use social comparisons because smart meters are not yet widely adopted. However, it is possible to highlight the behavior, not of the majority but, of peers. This approach is based on *social identity*, which aims to make the behavior of one or several peers more salient in order to influence their decision in the direction of peer action. Indeed, empirical evidence in psychology (Goldstein and Cialdini, 2007; Swann Jr and Bosson, 2010; Rogers et al., 2018) have emphasized that agents are more likely to follow a norm if they perceive themselves as being close to the individual/group of reference.

3 Experimental design

As explained in the introduction, we combine a choice experiment (part 3.1) with treatments (part 3.2).

3.1 Discrete Choice Experiment (DCE)

In order to elicit farmers' preferences regarding smart water meters, we use a choice experiment (see section 3.1.1). In this study, we propose multiple choice cards and for each choice card, farmers have to choose between three options : two different alternatives of smart water meters and a status quo (SQ) option. The latter correspond to their current situation, *i.e.*, their current water meter. The two smart water meters alternatives are described in terms of attributes, each alternative presenting different level of these attributes (see part 3.1.2).

3.1.1 Choice modelling

According to Lancasters' theory (Lancaster, 1966) and the Random Utility Model - RUM (McFadden et al., 1973), farmers' decisions to choose a smart water meter or to stay with a mechanical one will result from the relative utility they derive from the different alternatives, *i.e.*, respondents are going to choose the alternative to obtain the highest (expected) utility. The RUM model assume that a farmer i ($i = 1, ..., I$) choose among j ($j = 1, ..., J$) possible multi-attribute water meters, and the associated utility U_{ijt} from alternative j in choice card t ($t = 1, ..., T$) is:

$$U_{ijt} = V_{ijt} + \epsilon_{ijt} \tag{1}$$

where V_{ijt} is the indirect utility from choosing water meter j, and ϵ_{ijt} is the error term capturing unobserved utility.

The conditional logit model (CL) has been widely used to explain the respondents' decisions in choice experiments. In this approach, the utility writes:

$$U_{ijt} = \beta_i X_{ijt} + \epsilon_{ijt} \tag{2}$$

with X_{ijt} the vector of attributes of the water smart meter, β are the parameters to be estimated, and ϵ the random unobserved utility component. This model assumes that error terms, ϵ, are independently and identically distributed (IID) across the population and irrelevant alternatives are independent (IIA). It is assumed that respondents are homogeneous in their taste parameter estimates. The IIA assumption can be tested using the hausman test.

More recently, numerous studies have shown that this can be too restrictive for the discrete choice analysis (Train, 2003), accounting for the unobserved heterogeneity in tastes and preferences (Zhang and Sohngen, 2018). Indeed, the mixed multinomial logit model (MNL) (McFadden and Train, 2000) and the latent class model (LCM) are among the most used models, allowing the heterogeneity of preferences and relaxing the IIA property. In the MNL, farmer i's utility ($i = 1, ..., I$) from choosing alternative j ($j = 1, ..., J$) in choice card t ($t = 1, ..., T$) is given by :

$$U_{ijt} = (\beta_i + \gamma_i)X_{ijt} + \epsilon_{ijt} \tag{3}$$

With γ a farmer i's specific vector, and ϵ is still considered IID.

Following the analysis of the attributes that explain farmers' water meters' choices, we calculate farmers' WTP for attribute x. WTP is given by:

$$WTP_{jt} = \frac{-\beta_x}{\beta_{price}} \tag{4}$$

β_x and β_{price} are the parameters associated with attribute x and the monetary attribute, *i.e.*, the price of the water meters, respectively.

3.1.2 Choice Experiment Attributes and Design

This work is part of a regional project which aims at understanding and improving the adoption of smart water meters by farmers. As part of this project, we benefited from a partnership with local stakeholders and water managers. Thus, we conducted a first field survey (between may and june 2019) in the southwest of France in order to understand the characteristics of the meters sought by farmers and useful for water managers. This preliminary work allowed us to identify five relevant attributes and their levels (see table 1) for local stakeholders and farmers.

The first attribute, *information*, is the access to the average water consumption of the other farmers in the respondent geographic sector. This allows farmers to compare themselves and, therefore, to adapt, or not, their consumption. Such piece of information was used in studies to reduce electricity or water consumption (Schultz et al., 2007; Allcott, 2011; Costa and Kahn, 2013; Ferraro and Price, 2013; Brent et al., 2016). The second attribute, *alert*, is a message received in the case of abnormal water consumption. This alert allows farmers to be informed in the case of a leak or a fraudulent tie-up. Local stakeholders and farmers were particularly in favor if this attribute during our meetings. The third attribute, *confidentiality*, is related to the confidentiality on individual data and historic consumption. This attribute proposes a total confidentiality of the daily consumption registered by the smart meters (*i.e.*, only made available to the local manager in order to manage the water dams in the sector). Indeed, several studies have emphasized that privacy concerns may decrease the likelihood to adopt new technologies: instant messaging (Lowry et al., 2011), biometrics (Miltgen et al., 2013) or mobile apps (Gu et al., 2017) are examples in which privacy concerns constitute one of the main determinants of users adoption. The fourth attribute is the conditional subsidy associated with a purchase of smart water meter. Three levels for this subsidy are determined: no subsidy *versus* two, low and high, levels of subsidy, 300 € or 600 €. The fifth attribute is the monetary attribute, the purchase price of the smart meter: 250 €, 500 €, 750 €, 1000 €, 1250 €, 1500 €. This price relates to a water smart meter equivalent to the respondent current meter in terms of average lifespan (*i.e.*, 10 years), diameter, flow rate, etc.

The status quo is defined as the current situation in terms of mechanical water meters (see Table 1) : mechanical meters have no information on the others' consumption, no alert in the case of abnormal water consumption and no daily consumption information, so the confidentiality, as defined in this study, is respected. Of course, they no not receive subsidy and there is no additional cost to keep their current mechanical water meter.

Table 1: Attributes description and level

Attributes	Description	Levels	SQ
Information	Information on the average consumption of other farmers in the respondent's sector	No (ref.) Yes	No
Alert	Alert received on abnormal water consumption	No (ref.) Yes	No
Confidentiality	Water consumption historic is confidential, limited access to the farmer	No (ref.) Yes	Yes
Price	Purchase price of the smart-meters	250 €, 500 €, 750 €, 1000 €, 1250 €, 1500 € (continuous var.)	0 €
Conditional Subsidy	Subsidy conditional on i) smart meters adoption ii) a given proportion of farmers in the respondents' sector adopt the smart-meters	No subsidy (ref.) 300 € 600 €	No

Finally, the NGene software package (Rose et al., 2010) is used to generate an efficient design which minimizes the required sample size and choice cards number. Then, three blocks of six choice cards are generated.

3.2 Treatments

We propose two incentive instruments simultaneously tested: one to test three different thresholds of a conditional subsidy (part 3.2.1) and the other to test two types of nudges with a baseline (part 3.2.2). As presented in Table 2, combining our two instruments which have three treatments each, we finally obtain nine treatments. Each respondent is randomly directed toward a single treatment (between subject design).

3.2.1 Conditional subsidy with threshold treatments

As presented previously, one attribute of the choice experiment is the possibility to receive a conditional subsidy. The monetary subsidy received by a farmer who adopts a smart meter is conditional on the rate of farmers in the area who also adopt the smart meter. In the choice experiment, we consider two levels of subsidy (300 € and 600 €) to test the impact of the level of the amount of money. To deepen the analysis of this incentive instrument, we also test different threshold levels. Indeed, previous studies consider a threshold at 50% (Kuhfuss et al., 2016). But what would be the impact of this conditional subsidy if the announced threshold to reach is lower or higher? To test this parameter of the instrument we build three treatments corresponding to three versions of the questionnaire. The threshold in the reference treatment is set to 50%. In the low treatment, the threshold is set at 25%, while in the high treatment it is set at 75%.

In the low treatment, the 25% threshold may appear more realistic than a 50% threshold as this new technology is still very little developed. This low threshold can also suggest that the development of smart meters may take time before to become the majority. Conversely, the announcement of the high threshold (where farmers receive the subsidy if at least 75% of farmers adopt smart meters) may lead some farmers to believe that the 75% target desired by the public authorities is rapidly achievable and that there may therefore be a real enthusiasm for smart meters. Of course, a low threshold seems easier to reach, whereas a high threshold may appear unattainable and can lead to discouragement. Consequently, the different thresholds can have at least two opposite impacts on farmers' WTP for the subsidy. Either way, the different thresholds may change farmers' beliefs about the adoption rate and thus farmers' decision about smart meters.

3.2.2 Nudge treatments

In addition to a baseline, we implement two different types of nudges : a "cocktail" and a "testimony". The nudge part in the questionnaire is presented in Appendix A.1

The first nudge consist of what we call a "cocktail" (see appendix A.1.1): first, the respondents were reminded the existence of water restrictions. Then, they had to indicate to which extent they consider water management as important and, finally, to which extent they would be willing to commit to adopt a better water management. The first question can be seen as a *priming* question, while the second one is directly inspired from the theories of *commitment*. We follow the suggestion made by Dolan et al. (2012) in combing different types of nudges to increase their efficiency.

The second nudge is a "testimony" made by a farmer in the region Occitanie (see Appendix A.1.2). In this testimony, the farmer indicates that thanks to the adoption of smart water meters in his sector, it has been possible to reduce water losses by 15% to 20% annually (representing around 15,000 € annually). He also indicates that it has been possible because these smart meters are more accurate and because they allow to detect if there is water leakage. This written testimony goes with the name and the age of the farmer as well as his photo [3]. The latter aims to give credibility and realism to this testimony. This second nudge deals with farmers' *social identity*. Therefore, showing an example of a farmer having already adopted such a smart meter, we expect the respondents to identify to this farmer and to choose more often alternatives with the smart meter.

4 Data

4.1 The discrete choice survey

The questionnaire was programmed using the web-platform LimeSurvey (version 2.5). It includes five parts : introduction of the study and description of attributes, CE *per se*, follow-up questions (see below the paragraph on "protest"), definition of the status quo (see part 3.1.2) and beliefs elicitation (see part 4.3). The CE specific part is composed by six different choice cards successively proposed to respondents who, therefore, have six

[3] In the appendix the photo is hidden for the dissemination of the article but his face was visible in the questionnaire

choices to make between two different smart meters, "Meter 1" and "Meter 2", and an option "I keep my current meter". An example of a choice card is presented in Figure 1.

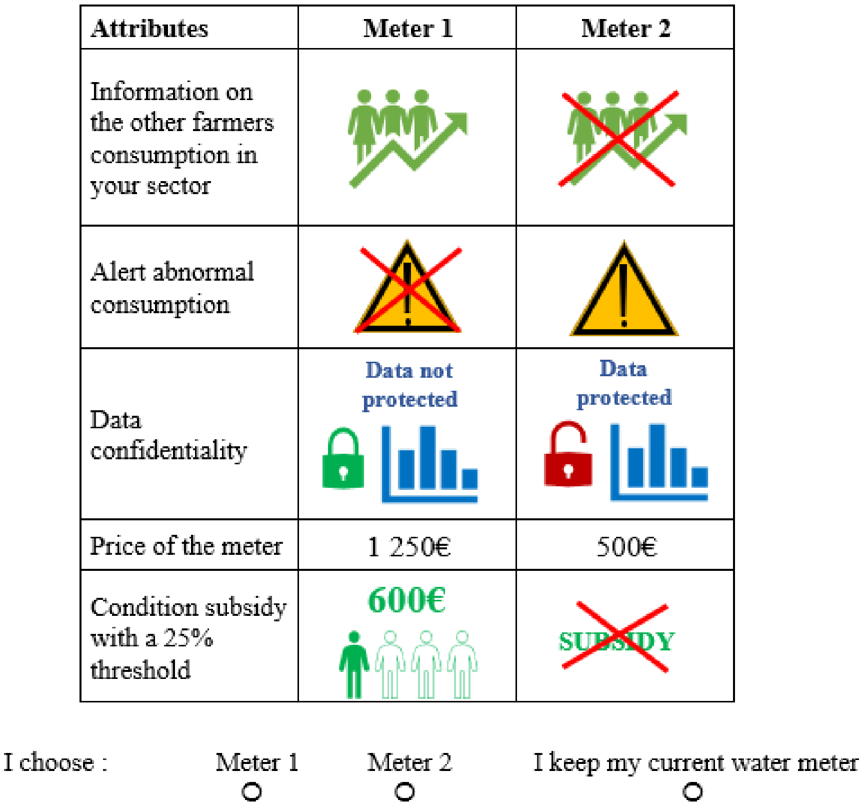

Figure 1: Example of a choice card.

First, two pilots, both on 1000 farmers, were conducted in June and September 2019. Combining the two pilots respondents, we obtained 21 completed questionnaires and then 126 observations. Our priors were estimated on this first pool of observations and the questionnaire was modified according to these first feedback.

Then, the link of the questionnaire has been sent by email[4], from November to December 2019, by a french pooling organization[5] to a mailing list of 90,000 farmers across France. This significant mailing list represents almost 20% of the total number of farmers in France. The time to complete the questionnaire is 15-20 minutes and the collected completed questionnaires are anonymous.

[4]The web-based survey is relevant for this type of study, 71% of French farmers having an internet connection in 2012 according to the French National Institute of Statistics and Economic Studies (INSEE). Moreover, this method allows to reach a large sample and limit the bias linked to interviewers (Vaissière et al., 2018).

[5]The company BVA (https://www.bva-group.com/)

The link of the questionnaire was sent through an introductory e-mail informing that the study was designed by the French Institute for Agricultural Research (INRA), for a project on water management and new technologies. Moreover, to motivate farmers to participate to our study, and based on the results of previous studies (Brennan et al., 1993; Deehan et al., 1997; Deutskens et al., 2004), we informed them that we would give 20 € to a charitable organization (Secours Populaire) for each set of hundred questionnaires completed. We chose this charitable organization as it is popular enough without being directly related to farmers.

4.2 Sample and descriptive statistics

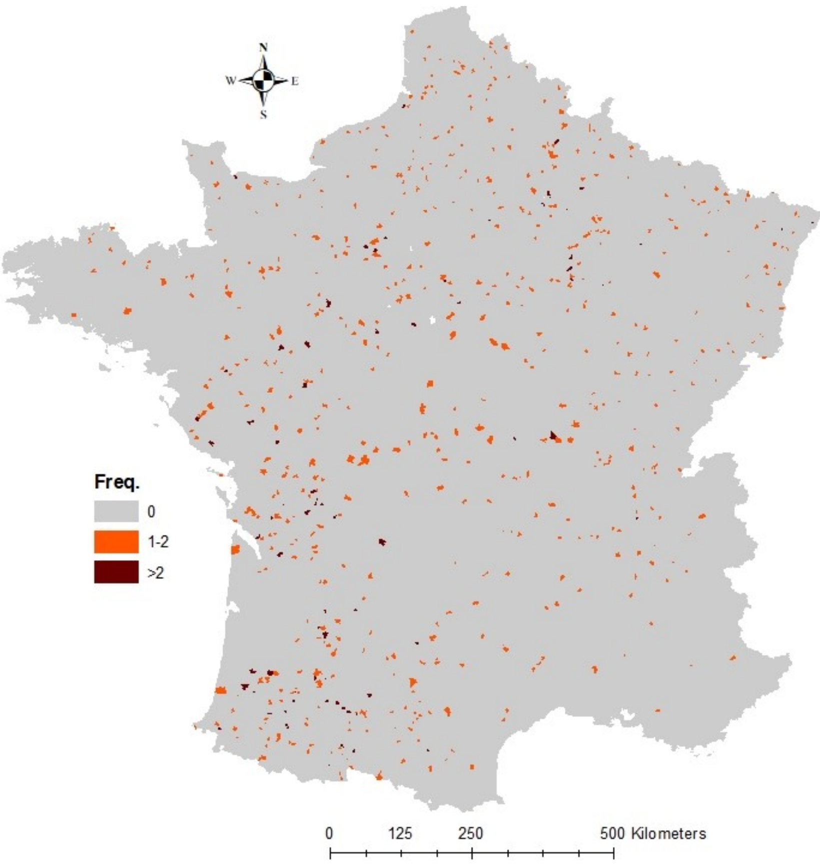

Figure 2: Spatial distribution of sampled Farmers (France)

1,613 farmers have completed the questionnaire which corresponds to almost a 2% response rate. The "protest" and "incomprehension" answers, identified by the follow up questions, represent 242 respondents in total. They are removed from our sample. Moreover, the 99 respondents who already declared having a smart meters are also removed. Indeed, this work aims at understanding the mechanisms and instruments that could increase the voluntary adoption of water smart meters. Farmers who already have a smart meter are not the target farmers of our study. Our final sample is therefore composed by 1,272 respondents across France.

Descriptive statistics on this final sample and the French agricultural census (2010) are presented in Appendix A.2. We observe an over-representation of young man (< 40 years old) with high degree of education (*i.e.*, masters degree) in field crop and polyculture activities in our sample. However, we have a acceptable spatial distribution representativeness of our sample at the French scale, as shown by Figure 2.

Table 2 summarizes the number of respondents in the nine treatments (subsidy thresholds and nudges). This design allows to study the impact of the conditional subsidy and on the nudges on smart meters' adoption.[6] All the treatments characteristics (gender, age, education, orientation, profit) are presented and compared in Appendix A.2. Overall, there are very few significant differences between our treatments. The most significant one is that "Cocktail" group has a higher proportion of men than in the "Baseline" and "Testimony" groups.

Table 2: Summary of observations in each treatment

	Baseline	Cocktail	Testimony	Total
Threshold 25%	125	168	109	402
Threshold 50%	141	181	115	437
Threshold 75%	155	167	110	433
Total	421	516	335	1,272

4.3 Farmers' beliefs on smart meters adoption rates

In a context of imperfect information decision, individuals must often rely on their beliefs, anticipations and perceptions in order to fulfill this information gap (Manski, 2004; Costanigro and Onozaka, 2020). Farmers may not want a smart meter because they don't believe in this technology. Likewise, they may not be sensitive to the conditional subsidy if they do not believe reaching the conditional threshold.

The subsidy in our scenarios being conditional, we ask the respondents on their beliefs regarding their perceived probability that the other farmers in their sector would adopt

[6] However, the estimation of the additional effect of both nudges are not allowed by this experimental design

the smart meter under this mechanism. These questions allow us to understand what are the farmers' subjective beliefs related to smart meters' adoption and how these beliefs affect their choice (for the SQ option or smart meters ones) and their WTP.

Then, into the questionnaire and after the part related to the choice experiment, an hypothetical context, composed by a smart meter's price of 750 € and a subsidy of 300 € paid for the purchase of a smart meter conditional upon reaching a collective adoption threshold, is presented. Farmers must answer the question: how many will adopt the smart meters out of 100 farmers in your sector? The question is first asked with the threshold proposed for the conditional subsidy in the CE. Then, to better control for the potential impact of the given conditional threshold on beliefs, the same question is asked two more times with the others thresholds. An example is provided with Figure 3.

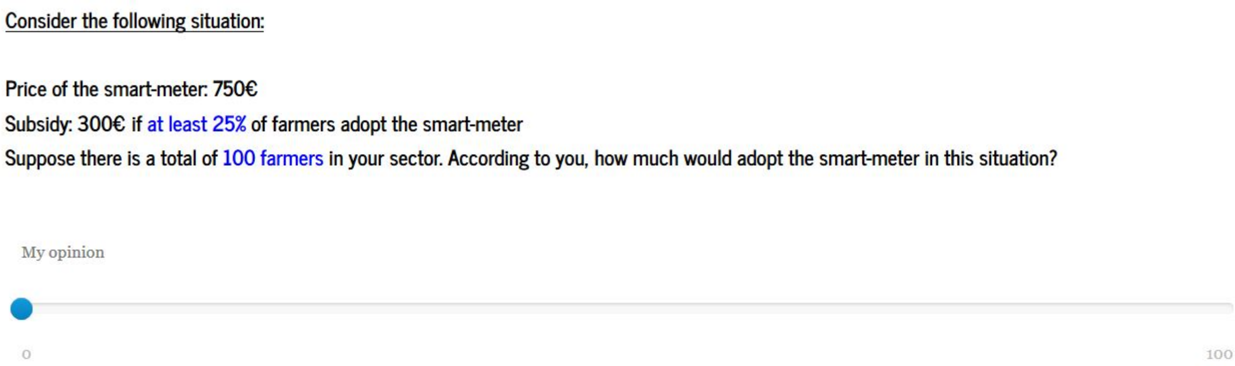

Figure 3: Elicitation of belief

Table 3: Beliefs according to the threshold treatments

	Belief questions			
Treatment groups	Belief 25	Belief 50	Belief 75	"Optimists"
Threshold 25%	**26.0**	26.2	26.1	48%
Threshold 50%	30.5	**29.1**	27.8	24%
Threshold 75%	34.6	32.7	**31.5**	7%

Notes : Two statistics are presented in this table: (i) the average of the respondents' beliefs for each of the three questions, studied by subsidy treatment groups (*i.e.*, threshold 25%; 50% and 75%) and, (ii) the percentage of respondents who have a higher belief or equal to the threshold proposed to them in the choice, named "Optimist".

A descriptive statistical analysis is first conducted on beliefs. Based on Table 3, we can make two observations. First, the means significantly increase with the subsidy thresholds treatments (see Appendix 3 for detailed statistics). This can be the result of an anchoring bias linked to the treatment related to the subsidy threshold group fixed at 25%, 50% or 75%. The threshold treatments have a significant effect on the farmers' beliefs on smart meters adoption rates. This question is then further explored in the following section on estimations and results. Second, within each treatment, the beliefs are quite stable with the threshold rate: we observe a weak decrease from 30.5 to 27.8 for the treatment "Subsidy 50%" and from 34.6 to 31.5 for the treatment "Subsidy 75%", but no change for "Subsidy 25%". In addition, we observe that the "optimists", *i.e.*, those who think that their subsidy threshold will be reached, are almost 50% in the 25% treatment but only 7% in the 75% treatment. Almost one fourth of the farmers in the 50% treatment believe that the 50% threshold will be reached.

5 Results

5.1 Mixed logit results

The results of conditional logit (CL) estimations are presented in Appendix A.4. We observe that the coefficients of the attributes, as well as those for the subsidy and the two instruments, are significant and with the expected signs. However, given the result of the hausman test concluding that the IIA assumption has been violated, and the very strong heterogeneity on our estimators (*i.e.*, all standard deviations with the mixed logit estimations are strongly significant), we focus on the results of the mixed logit (ML) models.

In Table 4, we report the results of mixed logit estimations considering the full sample. In the first model, we estimate a simple model without considering the effects of the nudges and of the subsidies thresholds. In the second model, we interact the alternative specific constant (ASC) for the SQ with the level of the conditional subsidy threshold treatment. We consider 50% as the reference, as it is the standard tipping point in the literature (Kuhfuss et al., 2016). Once this threshold is reached, adopting a smart meter is the norm. Above (below) 50%, and following our previous discussions, adopting the smart meter is (not yet) the norm but, at the same time, obtaining the conditional subsidy (does not) requires adoption from a lot of farmers inducing a (incentive) discouragement effect. In the fourth model we assess the global effect of nudges on the choice of the SQ, abstracting from the effects of the threshold of the conditional subsidy. Finally, the fifth model is a replication of the fourth one including an interaction between the ASC for the

SQ with the "optimist" respondents (see part 4.3) in each subsidy threshold group[7].

We obtain that all the coefficients associated to the attributes are significant and with the expected sign in all models, except for the attribute related to the possibility to receive information on the other farmers' water consumption. This could be explained by a strong response heterogeneity, as we can see on the SD part of Table 4. The respondents have a preference for the possibility to have an alert in case of abnormal water consumption and for the confidentiality of their data (positive and significant coefficient for these two attributes). Moreover, they prefer to pay less (negative and significant coefficient associated to the price attribute) and the two levels for the subsidy have positive and significant coefficient, which means that, independently of the level of the threshold, the subsidy has, on average, a significant impact on farmers' choices although the payment of the subsidy is conditional. Since the coefficient associated with the higher subsidy (600 €) is more than twice the coefficient of the subsidy of 300 €, the WTP for the subsidy may not be linear. In the second model, relatively to a 50% threshold level of adoption, the two other thresholds (25% and 75%) do not have a significant effect on the choice of the SQ. Controlling for the "optimist" respondents in the last model, we obtain that those who believe that the threshold to obtain the conditional subsidy will be reached significantly choose less often the SQ whatever the threshold. In addition, the coefficient is significantly higher for the treatment "threshold 75%" than the others. Finally, in the third model, both nudges induce the respondents to significantly choose less often the SQ than in the baseline. This is a first clue that they may be useful as communication tools to give incentive farmers to adopt smart meters.

How complement are the conditional subsidy and the nudges?

In Table 5, we report the results of mixed logit estimations per conditional subsidy threshold to assess whether the smart meters attributes and the implemented nudges have the same effect across the threshold treatments. This step allow us to determine how complement are these combinations of monetary and non-monetary incentives. We separate estimations for each threshold and we control, in each case, for the "optimists". Similarly to the previous results in Table 4, we find that all attributes are valued by the

[7]Different variables related to the belief response has been tested : dummy variable if the threshold associated to the treatment group is reached, mean belief, continuous variable, difference between belief and treatments' threshold. The results are stable across the different belief variables. The dummy variable is then selected.

Table 4: Mixed logit estimations.

	(1)	(2)	(3)	(4)	(5)
Mean					
Information	-0.0518	-0.0540	-0.0348	-0.0513	-0.0414
	(0.078)	(0.078)	(0.077)	(0.078)	(0.076)
Alert	1.767***	1.770***	1.753***	1.772***	1.743***
	(0.082)	(0.082)	(0.081)	(0.082)	(0.080)
Confidentiality	1.304***	1.302***	1.296***	1.303***	1.291***
	(0.091)	(0.091)	(0.091)	(0.091)	(0.090)
Price (in K€)	-1.639***	-1.640***	-1.628***	-1.640***	-1.614***
	(0.073)	(0.073)	(0.072)	(0.073)	(0.072)
Subs.300	0.490***	0.490***	0.491***	0.491***	0.489***
	(0.085)	(0.085)	(0.085)	(0.085)	(0.085)
Subs.600	1.104***	1.106***	1.111***	1.108***	1.094***
	(0.072)	(0.072)	(0.072)	(0.072)	(0.071)
SQ	0.666***	0.801***	0.982***	1.125***	1.470***
	(0.116)	(0.169)	(0.167)	(0.209)	(0.217)
SQ×Thresh.25%		-0.248		-0.231	0.311
		(0.216)		(0.215)	(0.268)
SQ×Thresh.75%		-0.170		-0.176	-0.382*
		(0.210)		(0.213)	(0.216)
SQ×Cocktail			-0.453**	-0.483**	-0.469**
			(0.198)	(0.202)	(0.200)
SQ×Testimony			-0.526**	-0.514**	-0.419*
			(0.235)	(0.236)	(0.224)
SQ×Thresh.25%×Belief					-1.810***
					(0.308)
SQ×Thresh.50%×Belief					-1.637***
					(0.343)
SQ×Thresh.75%×Belief					-2.839***
					(0.792)
SD					
Information	1.363***	1.365***	1.348***	1.362***	1.303***
	(0.115)	(0.116)	(0.113)	(0.115)	(0.112)
Alert	1.216***	1.217***	1.195***	1.219***	1.153***
	(0.098)	(0.098)	(0.098)	(0.099)	(0.097)
Confidentiality	1.623***	1.630***	1.617***	1.633***	1.605***
	(0.116)	(0.117)	(0.113)	(0.117)	(0.116)
Subs.300	-0.468**	-0.474**	-0.379	-0.461**	-0.370
	(0.228)	(0.226)	(0.302)	(0.234)	(0.345)
Subs.600	0.660***	0.660***	-0.666***	0.665***	0.651***
	(0.139)	(0.137)	(0.131)	(0.137)	(0.137)
SQ	2.519***	2.508***	2.426***	2.475***	2.314***
	(0.117)	(0.119)	(0.126)	(0.122)	(0.119)
SQ×Thresh.25%		-0.445		-0.484	0.785*
		(0.419)		(0.404)	(0.414)
SQ×Thresh.75%		0.102		0.118	0.158
		(0.350)		(0.359)	(0.364)
SQ×Cocktail			0.271	-0.416	-0.292
			(0.428)	(0.409)	(0.302)
SQ×Testimony			1.039*	0.0425	-0.546
			(0.562)	(0.561)	(0.474)
SQ×Thresh.25%×Belief					-0.445
					(0.521)
SQ×Thresh.50%×Belief					0.324
					(1.209)
SQ×Thresh.75%×Belief					2.548***
					(0.880)
N	22896	22896	22896	22896	22896
ll	-5875.8	-5874.6	-5872.5	-5870.5	-5831.6

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

respondents, except the possibility to receive information on the other farmers' water consumption. Our main result is that respondents significantly choose less often the SQ under the implementation of the nudges (both the cocktail and the testimony) only when the threshold of the conditional subsidy is 75% (significant effect at the 10% level only, and 1% for the testimony when beliefs are not taken into account). This result seems to indicate that both incentives are complement when respondents are proposed high thresholds for the conditional subsidy, *i.e.*, if the regulator wants the adoption of smart meters to be the norm among farmers.

To better understand this synergy between our nudges and the conditional subsidy, we now propose symmetric estimations holding the type of nudge fixed and varying the conditional subsidy thresholds and amounts: we interacted the amounts of the subsidy with the possible thresholds. The results are reported in Table 6.

Again, we find that the coefficients of the attributes *Alert*, *Confidentiality* and *Price* are significant and with the expected sign. However, regarding the possibility to receive information on the other farmers' water consumption, it appears that the coefficient of this attribute is negative and significant (at the 1% level) in the baseline and positive and significant (at the 5% level) in the testimony treatment. Our first observation is therefore that the testimony seems to change farmers' perception regarding this attribute. This may be explained by the content of our nudge: in his testimony, the farmer emphasized the collective benefits that were made possible thanks to the smart water meters (reduction of counting losses for the local farmers' association, detection of leakages, etc.). Farmers in that treatment may perceive this attribute as necessary to benefit from these advantages. Regarding the effect of the amounts of the subsidy and their adoption thresholds, we find that the coefficients of these variables are always positive and significant (at the 1% level) for a 600 € subsidy, whatever the adoption threshold. Moreover, except in the testimony treatment, farmers are willing to pay more for this attribute with a 75% threshold, although this requires more farmers to adopt water smart meters. Regarding the 300 € subsidy, the results are not stable depending on the type of model considered. The second result of this analysis is therefore that our nudges appear to be complement to high subsidies. Moreover, in the case of the testimony, it seems possible to use this type of non-monetary incentive to better communicate on the utility of smart meters, as it may change the respondents' perception of the attributes (for the *Information* attribute in our case).

Table 5: Mixed logit estimations.

	Threshold 25%		Threshold 50%		Threshold 75%	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean						
Information	-0.0388	-0.0219	-0.149	-0.166	0.0374	0.0332
	(0.145)	(0.138)	(0.137)	(0.138)	(0.122)	(0.123)
Alert	1.805***	1.756***	1.722***	1.708***	1.823***	1.828***
	(0.157)	(0.150)	(0.137)	(0.135)	(0.140)	(0.140)
Confidentiality	1.155***	1.135***	1.119***	1.101***	1.654***	1.670***
	(0.163)	(0.158)	(0.151)	(0.152)	(0.160)	(0.162)
Price (in k eur.)	-1.742***	-1.687***	-1.723***	-1.731***	-1.508***	-1.512***
	(0.136)	(0.132)	(0.129)	(0.132)	(0.120)	(0.120)
Subs. 300	0.374**	0.340**	0.473***	0.464***	0.614***	0.621***
	(0.159)	(0.159)	(0.146)	(0.148)	(0.147)	(0.148)
Subs. 600	1.044***	1.007***	1.111***	1.120***	1.221***	1.224***
	(0.134)	(0.129)	(0.123)	(0.124)	(0.123)	(0.123)
SQ	0.796**	1.632***	0.901***	1.316***	1.230***	1.375***
	(0.320)	(0.331)	(0.309)	(0.314)	(0.261)	(0.264)
SQ×Cocktail	-0.366	-0.406	-0.317	-0.339	-0.613*	-0.601*
	(0.382)	(0.362)	(0.366)	(0.361)	(0.317)	(0.319)
SQ×Testimony	-0.306	-0.296	-0.180	-0.0254	-0.743**	-0.694*
	(0.413)	(0.381)	(0.421)	(0.407)	(0.368)	(0.362)
SQ×Belief		-1.816***		-1.903***		-3.004***
		(0.318)		(0.365)		(0.744)
SD						
Information	1.552***	1.445***	1.481***	1.532***	1.010***	1.008***
	(0.195)	(0.190)	(0.191)	(0.193)	(0.213)	(0.222)
Alert	1.423***	1.257***	1.097***	1.118***	1.245***	1.241***
	(0.181)	(0.177)	(0.186)	(0.183)	(0.172)	(0.169)
Confidentiality	1.795***	1.689***	1.446***	1.431***	1.635***	1.660***
	(0.214)	(0.206)	(0.214)	(0.205)	(0.192)	(0.198)
Subs. 300	-0.665*	-0.814**	-0.234	-0.312	-0.705**	-0.726**
	(0.375)	(0.318)	(0.375)	(0.324)	(0.311)	(0.309)
Subs. 600	0.770***	0.662***	-0.645***	-0.660***	0.736***	0.715***
	(0.219)	(0.213)	(0.208)	(0.224)	(0.205)	(0.205)
SQ	2.485***	2.187***	2.657***	2.597***	2.256***	2.128***
	(0.246)	(0.272)	(0.217)	(0.207)	(0.191)	(0.207)
SQ×Cocktail	1.319**	1.609***	0.311	0.247	-0.194	0.485
	(0.516)	(0.494)	(0.372)	(0.363)	(0.796)	(0.837)
SQ×Testimony	-0.138	0.804	1.071	-0.489	1.011	0.946
	(0.655)	(0.630)	(0.764)	(0.810)	(0.657)	(0.649)
SQ×Belief		-0.214		0.135		2.197
		(0.525)		(1.179)		(1.463)
Number of obs.	7236	7236	7866	7866	7794	7794
Log-likelihood	-1865.5	-1849.0	-1957.2	-1943.1	-2029.0	-2017.3

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robustness tests

In some choice cards the conditional subsidy is higher than the price, so the final cost of the smart meter may be negative. In this case, some respondents may think that

Table 6: Mixed logit estimations.

	Baseline		Cocktail		Testimony	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean						
Information	-0.451***	-0.446***	-0.0155	-0.0238	0.315**	0.301**
	(0.156)	(0.154)	(0.123)	(0.122)	(0.138)	(0.136)
Alert	1.784***	1.759***	1.729***	1.710***	1.927***	1.895***
	(0.155)	(0.153)	(0.126)	(0.126)	(0.164)	(0.159)
Confidentiality	1.375***	1.382***	1.513***	1.482***	1.158***	1.142***
	(0.169)	(0.167)	(0.153)	(0.151)	(0.169)	(0.167)
Price (in k€)	-1.896***	-1.856***	-1.678***	-1.661***	-1.486***	-1.461***
	(0.143)	(0.140)	(0.117)	(0.115)	(0.133)	(0.131)
Subs.300×Thresh.25%	0.481*	0.352	0.596***	0.494**	0.0492	-0.0796
	(0.267)	(0.279)	(0.210)	(0.210)	(0.285)	(0.291)
Subs.300×Thresh.50%	0.520**	0.521**	0.304	0.284	0.740***	0.722***
	(0.247)	(0.242)	(0.198)	(0.198)	(0.267)	(0.265)
Subs.300×Thresh.75%	0.464*	0.444	0.733***	0.808***	0.503*	0.621**
	(0.278)	(0.286)	(0.204)	(0.204)	(0.295)	(0.290)
Subs.600×Thresh.25%	1.011***	0.920***	1.119***	1.021***	0.889***	0.785***
	(0.229)	(0.226)	(0.183)	(0.180)	(0.223)	(0.222)
Subs.600×Thresh.50%	1.212***	1.190***	1.058***	1.036***	1.184***	1.156***
	(0.204)	(0.201)	(0.175)	(0.171)	(0.208)	(0.206)
Subs.600×Thresh.75%	1.338***	1.380***	1.191***	1.260***	1.053***	1.124***
	(0.217)	(0.215)	(0.177)	(0.179)	(0.219)	(0.218)
SQ	0.743***	1.142***	0.512***	0.865***	0.741***	1.247***
	(0.221)	(0.231)	(0.175)	(0.186)	(0.230)	(0.248)
SQ×Belief		-1.650***		-1.406***		-1.836***
		(0.416)		(0.298)		(0.396)
SD						
Information	1.536***	1.495***	1.445***	1.454***	1.008***	0.981***
	(0.210)	(0.209)	(0.173)	(0.174)	(0.261)	(0.253)
Alert	1.334***	1.248***	1.255***	1.229***	1.192***	1.121***
	(0.179)	(0.186)	(0.159)	(0.159)	(0.181)	(0.178)
Confidentiality	1.688***	1.638***	1.789***	1.732***	1.625***	1.574***
	(0.225)	(0.219)	(0.188)	(0.182)	(0.205)	(0.199)
Subs.300×Thresh.25%	-0.749	-0.896	0.441	0.422	0.566	0.575
	(0.527)	(0.565)	(0.564)	(0.671)	(0.645)	(0.631)
Subs.300×Thresh.50%	-0.212	-0.212	0.0324	0.217	-0.00404	0.0396
	(0.511)	(0.461)	(1.425)	(0.668)	(0.550)	(0.501)
Subs.300×Thresh.75%	-1.292***	1.489***	0.240	0.227	1.361***	1.264***
	(0.424)	(0.380)	(0.434)	(0.433)	(0.470)	(0.444)
Subs.600×Thresh.25%	0.771**	0.698	0.755**	0.658**	0.897**	0.878**
	(0.383)	(0.443)	(0.302)	(0.301)	(0.387)	(0.362)
Subs.600×Thresh.50%	0.447	0.444	0.787***	-0.719**	0.402	0.393
	(0.442)	(0.436)	(0.305)	(0.313)	(0.458)	(0.478)
Subs.600×Thresh.75%	1.047***	-1.027***	0.540	0.574*	0.917***	0.906***
	(0.323)	(0.333)	(0.348)	(0.328)	(0.346)	(0.331)
SQ	2.856***	2.560***	2.227***	2.145***	2.699***	2.570***
	(0.234)	(0.220)	(0.160)	(0.159)	(0.238)	(0.230)
SQ×Belief		2.137***		-0.349		-0.500
		(0.575)		(0.929)		(0.570)
Number of obs.	7578	7578	9288	9288	6030	6030
Log-likelihood	-1836.7	-1824.4	-2441.4	-2429.0	-1566.4	-1555.4

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

every farmers will adopt a smart meter, and may consider that the rate of adoption can easily exceed the threshold. In some other cases, the threshold may seem impossible to reach. Therefore, two specific and extreme cases for robustness check is considered (Appendix A.5) : (i) given that the proposed subsidy is a conditional one, people may be very pessimistic about getting it, then we ignore this attribute (Table A.5); (ii) given that people may be very optimistic that the threshold can be reached, we consider the systematic obtaining of the subsidy and therefore the price-subsidy variable as a monetary attribute (Table A.6). The results remain unchanged.

5.2 Analysis of the WTP

Using the results from the previous subsection, we compute the WTP, defined by the marginal rate of substitution between the studied attribute and the monetary one, *i.e.*, the price. The WTP estimates presented in Table 7 are computed using the results of the mixed logit estimated by threshold and nudges groups, presented in Tables 5 and 6 respectively. The last column (all sample) is calculated using model (1) of Table 4.

The results within treatments show that respondents have, on average, a WTP of 400 € to stay with the status quo and to keep their mechanical meter (SQ variable), *i.e.*, they ask for 400 €, on average, to adopt a smart meter. However, when we include the WTP for the different smart meters attributes *Alert* and *Confidentiality* (*Information* is globally non-significant), the WTP becomes positive on average and is around 1700 € without subsidy. An option including a smart meters with specific attributes, such as the confidentiality of their data, can motivate farmers to move away from their current situation. Moreover, Table 7 shows that the estimated WTP related to the subsidy attribute are on average, and in most cases, greater than the amount of the proposed conditional subsidy (300 € or 600 €). These figures show that farmers value the subsidy more than its expected value. What is surprising is that the WTP for the subsidy (300 € or 600 €) in the three threshold treatments are not significantly different. Even if the 75% threshold is far from most farmers' expected rate of adoption, they value the subsidy quite high. Secondly, while the amount of the subsidy is doubled, from 300 € to 600 €, the WTP estimated is more than twice as high between the two amounts of this attribute.

From the results between treatments, we observe increasing trends for the WTP estimates for the 75% threshold groups (whatever the nudge) and for the "testimony" (whatever the threshold). Indeed, the total WTP (considering all attributes) are 30% higher for the 75% threshold compared to the others, and the WTP estimates are, on average, 40% and 60% higher, respectively for the cocktail and the testimony compared to the baseline (no nudge). However, these trends are not significantly different from each other with regard to standard errors. Only two specific estimates are significantly different from the others. First, the *confidentiality* for the 75% threshold corresponds to a WTP 70% higher than the other two thresholds (*i.e.* 25% and 50%). In addition, as highlighted in the previous subsection, the "testimony" treatment also emphasized the *Alert* attribute: compared to the "cocktail" treatment and the baseline, respondents in this treatment are willing to pay, on average, more than 200 € extra (the confidence intervals do not overlap). This confirms that nudging can be used as a communication tool to emphasize attributes.

Table 7: WTP for all treatment estimations

	Thres. 25%	Thres. 50%	Thres. 75%	Baseline	Cocktail	Testimony	All sample
SQ	457	523	816	392	305	498	406
	[140;773]	*[211;836]*	*[497;1135]*	*[183;601]*	*[122;489]*	*[221;776]*	*[279;534]*
Info	-	-	-	-238	-	212	-
	-	-	-	*[-373; -103]*	-	*[58; 366]*	-
Alert	1036	999	1209	941	1031	1297	1078
	[874;1199]	*[853;1146]*	*[1030;1388]*	*[796;1087]*	*[890;1172]*	*[1092;1502]*	*[986;1171]*
Confidentiality	663	649	1097	725	902	779	796
	[513;813]	*[514;785]*	*[913;1280]*	*[584;866]*	*[758;1046]*	*[590;968]*	*[706,885]*
Subs 300	214	275	407				299
	[68;361]	*[140;409]*	*[250;564]*				*[216;382]*
Subs 600	599	645	809				674
	[465;733]	*[518;772]*	*[655;963]*				*[596;753]*
SQ*Cocktail	-	-	-406				
	-	-	*[-755;-58]*				
SQ*Testimony	-	-	-493				
	-	-	*[-898;-87]*				
Subs 300 * Thres. 25%				254	355	-	
				[63;486]	*[152;559]*	-	
Subs 300 * Thres. 50%				274	-	498	
				[63;486]	-	*[208;789]*	
Subs 300 * Thres. 75%				245	437	339	
				[6;484]	*[241;633]*	*[15;662]*	
Subs 600 * Thres. 25%				533	667	598	
				[331;735]	*[481;852]*	*[342;855]*	
Subs 600 * Thres. 50%				639	631	797	
				[457;821]	*[453;809]*	*[555;1039]*	
Subs 600 * Thres. 75%				706	710	709	
				[511;901]	*[530;890]*	*[453;965]*	

Notes : The WTP, the mean and the confidence interval at a 95%, are computed from Tables 5 and 6, columns (1),(3) and (5), and the Table 4, column (1), respectively for the "Thresholds"" columns, "Nudges" columns and "All sample" column. When the results are non-significant, the WTP is not computed.

6 Discussion and conclusion

Although improving efficiency of water use in agriculture is a clear objective of the European CAP, water scarcity remains a critical issue in Europe. Agriculture must therefore both contribute to the mitigation of this problem and adapt to the expected increase in droughts. In this context, new technologies on water use, such as smart water meters, allow for a significant improvement of the irrigation and the water use for local water managers.

Therefore our study aims at : i) assessing the French farmers' WTP for specific characteristics of smart water meters and, ii) testing different monetary and non-monetary incentives instrument to encourage voluntary adoption of smart meters by farmers.

We propose an original approach combining a choice experiment with treatments to test different thresholds of a conditional subsidy and two types of nudges (a cocktail of nudges and a testimony) on French farmers.

We obtain three main takeaways. First, our results show that a smart meters including specific attributes can motivate farmers to move away from their current situation. Concretely, when the total WTP for the different smart meters attributes includes the *Alert* and *Confidentiality* attributes, the latter becomes positive. However, the results on the *Information* attribute are strongly heterogeneous, and thus mostly non-significant. In a sense, this is in line with the results obtained by Allcott and Kessler (2019) who show that, regarding the possibility to receive Home Energy Reports, 34% of the their respondents stated negative WTP. Second, our results uniquely show that the respondents are not discouraged by a very high threshold of 75%, on the contrary the higher the announced threshold for the conditional subsidy, the more farmers identify the adoption of smart meters as the social norm they wish to follow. Finally, subsidy and nudges appear to be generally effective, and in particular when a testimony nudge is associated to a high threshold conditional subsidy. Indeed, the conditional subsidy and our nudges appears to be complement: when combined with a high adoption threshold, our nudges perform better in the sense that farmers significantly choose less often the SQ option. In addition to this synergy, we show that our nudges generally perform better when associated to high amounts of subsidy.

This paper contributes to the literature which shows that individuals have a preference for the adoption of behavior which is in line with social norms. From a public policy point of view, our contribution is twofold. First, in our knowledge this is the first choice experiment conducted at the national scale with more than thousand farmers' responses. This allows to conclude more generally on the effects of incentive policies and their application to other case studies. Second, we provide guidelines for policies related to water management in agriculture. Our result indicates that the government has to disseminate information on the benefit and the development of the smart water meters (in a specialized journal or information bulletin for example), in order to convince other farmers to do the same.

This work has some limitations. One of the limitations, often associated with revealed preference methods, is that the declaration of intent is not the behavior observed. Potential strategic bias is standard in this type of study. However, concerning the incentives studied effects related to the conditional thresholds and to the nudges, as we randomly defined treatment groups, the relative response difference between control groups and the treatments are therefore clearly linked to the instruments. Another limitation deals with the subsidy cost. Given the public good dimension of the smart meter, the subsidy we proposed is financed by the regulator. However, with a subsidy of 600 € per farmers and an adoption threshold of 75% nationwide, the total amount would be extremely high. Therefore, this study does not define the targeting of a smart meters subsidy policy.

We conclude with directions that can be taken in future research. Further research is needed to explore other incentive instruments on smart water meters adoption. Indeed, in a free riding context, two monetary incentives tools can be used, a subsidy to reward the voluntary adoption of smart meter and a tax to punish free riding behavior. In this work we choose to test the subvention in the case of the adoption of smart meter. A possible development would be to study the effect of a tax on mechanical meter holders on the smart meters adoption. Finally, an additional study testing smart meter demand according to different costs scenarios (varying price and subvention) has to be conducted to conclude on targeted incentive instrument.

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A Appendix

A.1 Nudges

A.1.1 Cocktail

As an actor in your territory, you are aware of the fact that periods of water restriction during the summer is an environmental challenge and a shortfall for agriculture.

1. In that context, is water management important to you? (*"Yes, totally", "Rather yes", "Rather no", "Totally not"*)

2. Would you be willing to commit to better management of the water resource? (*"Yes, totally", "Rather yes", "Rather no", "Totally not"*)

In territories that are already equipped, smart meters allow for better management of water resources thanks to the precision and frequency of the records. Better counting also allows for greater equity among farmers.

A.1.2 Testimony

Testimony of Yves D., 59 years old, farmer in the Tarn et Garonne

Yves has been involved for more than 3 years in improving water management in his sector.

"Since we have installed smart meters in our sector, this has allowed us to significantly reduce counting losses for our local farmers' association, we have gone from 15% to 20% of annual losses to 3% today, which is about 15 000 euros of revenue for the association. Indeed, not only the smart meters are more accurate than the mechanical ones, but in addition they allow us to quickly see if there is a leak. We can more easily track our water consumption and better manage it. Water management has become more equitable between the different farmers of our local farmers' association. "

A.2 Descriptive Statistics

Variables	All	No nudge	Cocktail	Diff1	Testimony	Diff2.
Observations	1272	421	516		335	
Man	0.895	0.872	0.913	0.020^b	0.896	0.024
	(0.307)	(0.335)	(0.282)	(0.052)	(0.306)	(0.028)
Age						
Age < 40	0.219	0.209	0.213	0.027	0.242	0.031
	(0.414)	(0.407)	(0.410)	(−0.003)	(0.429)	(−0.022)
Age 40-59	0.638	0.660	0.645	0.031	0.600	0.035^c
	(0.481)	(0.474)	(0.479)	(−0.005)	(0.491)	(−0.016)
Age > 60	0.142	0.131	0.141	0.023	0.158	0.026
	(0.349)	(0.337)	(0.349)	(−0.011)	(0.365)	(−0.028)
Education						
No degree	0.006	0.002	0.008	0.005	0.009	0.005
	(0.079)	(0.049)	(0.088)	(−0.039)	(0.094)	(−0.046)
FCGE	0.004	0.007	0.004	0.005	0.000	0.005
	(0.063)	(0.084)	(0.062)	(0.022)	(0.000)	(0.084)
CAP or BEP	0.094	0.095	0.095	0.019	0.093	0.021
	(0.292)	(0.294)	(0.293)	(0.000)	(0.290)	(0.003)
GCE “A-Level”	0.270	0.259	0.287	0.029	0.257	0.032
	(0.444)	(0.439)	(0.453)	(−0.014)	(0.437)	(0.001)
BAC +2	0.478	0.475	0.475	0.033	0.487	0.037
	(0.500)	(0.500)	(0.500)	(0.000)	(0.501)	(−0.001)
BAC +5	0.145	0.154	0.130	0.023	0.155	0.027
	(0.352)	(0.362)	(0.336)	(0.025)	(0.363)	(−0.001)
Orientation						
Polyculture	0.475	0.500	0.477	0.033	0.438	0.037^c
	(0.500)	(0.501)	(0.500)	(0.001)	(0.497)	(0.004)
Field crops	0.374	0.345	0.374	0.032	0.408	0.036^c
	(0.484)	(0.476)	(0.484)	(−0.008)	(0.492)	(−0.016)
Market gardening	0.068	0.068	0.068	0.017	0.066	0.018
	(0.251)	(0.251)	(0.253)	(−0.001)	(0.249)	(0.003)
Viticulture	0.037	0.027	0.037	0.012	0.051	0.014^c
	(0.190)	(0.161)	(0.189)	(−0.028)	(0.220)	(−0.059)
Fruit production	0.039	0.024	0.039	0.012	0.057	0.014^b
	(0.194)	(0.154)	(0.194)	(−0.040)	(0.232)	(−0.079)
Cattle breeding	0.150	0.157	0.164	0.024	0.120	0.026
	(0.357)	(0.364)	(0.371)	(−0.007)	(0.326)	(0.039)
Sheep sector	0.018	0.022	0.012	0.008	0.024	0.011
	(0.134)	(0.146)	(0.108)	(0.038)	(0.153)	(−0.007)
Pig farming	0.046	0.075	0.033	0.015^a	0.030	0.017^a
	(0.210)	(0.264)	(0.180)	(0.084)	(0.171)	(0.093)
ALA	139.881	142.126	140.704	7.378	135.829	8.411
	(112.419)	(108.711)	(111.951)	(−3.241)	(117.760)	(−9.050)
Profit						
Profit $< 20KE$	0.373	0.352	0.391	0.032	0.373	0.035
	(0.484)	(0.478)	(0.489)	(−0.011)	(0.484)	(−0.006)
Profit 20-40KE	0.226	0.207	0.221	0.027	0.260	0.031^c
	(0.419)	(0.405)	(0.415)	(−0.010)	(0.439)	(−0.034)
Profit 40-60KE	0.082	0.086	0.083	0.018	0.075	0.020
	(0.274)	(0.280)	(0.277)	(0.003)	(0.263)	(0.017)
Profit $> 60KE$	0.086	0.105	0.070	0.018^c	0.090	0.022
	(0.281)	(0.306)	(0.255)	(0.051)	(0.286)	(0.020)

Notes: Difference between the "No nudge" group and the two nudged groups : Difference between "No nudge" and "Cocktail" (column 2 to column 4), and difference between "No nudge" and "Testimony" (columns 2, 5 and 6). French Certificate of General Education (FCGE), General Certificate of Education Advanced Level (GCE “A-Level”), Youth Training or BTEC First Diploma (CAP or BEP), Diploma of Higher Education (BAC+2) and Masters Degree (BAC+5), Arable Land Area (ALA). Standard errors in columns (2), (3) and (4) and standard deviations in columns (5) in brackets. ^{a}, ^{b}, ^{c} significant at the 1%, 5% and 10% level, respectively.

A.3 Various statistics

Table A.1: Descriptive statistics (final sample and agricultural census)

%	Choice Experiment	Agriculture Census (2010)
Gender		
Male	89,5	77,3
Age		
< 40	21,9	5,0
[40;60]	63,8	44,5
> 60	14,2	50,5
Education		
No degree	0,9	19,4
FCGE	0,4	26,9
CAP or BEP	9,4	28,9
GCE "A-level"	27,0	14,9
BAC+2	47,8	5,1
BAC+5	14,5	4,8
Activity		
Field crop	38,0	27,2
Polyculture	29,1	13,2
Viticulture	6,2	14,5
Market gardening	2,9	3,4
Fruit production	3,6	4,5
Cattle breeding	13,9	25,4
Sheep sector	6,4	11,7

Table A.2: Choice of SQ on six choice cards

SQ	All	Sub_25	Sub_50	Sub_75	Baseline	Cocktail	Testimony
0	23.7%	25%	24%	23%	23%	23%	27%
1	8.0%	9%	8%	7%	5%	10%	9%
2	8.8%	9%	8%	9%	7%	9%	11%
3	13.4%	14%	12%	14%	13%	15%	11%
4	15.1%	11%	16%	18%	16%	16%	14%
5	14.6%	15%	13%	15%	17%	13%	13%
6	16.4%	16%	19%	14%	19%	14%	16%
	100%	100%	100%	100%	100%	100%	100%

Table A.3: Descriptive Statistics on belief

	25% threshold	*Diff.1*	50% threshold	75% threshold	*Diff.2*
Belief_mean	26.1	*-3.05***	29.2	32.9	*3.78****
Sd	*20.6*	*(1.42)*	*20.6*	*22.3*	*(1.45)*

A.4 Conditional logit

Table A.4: Conditional logit estimations.

	(1)	(2)	(3)	(4)	(5)
choice					
Information	0.137***	0.137***	0.138***	0.138***	0.137***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Alert	1.142***	1.142***	1.145***	1.144***	1.151***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.042)
Confidentiality	0.690***	0.690***	0.692***	0.692***	0.697***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Price (in k€)	-1.016***	-1.016***	-1.017***	-1.016***	-1.020***
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Subs.300	0.408***	0.407***	0.408***	0.408***	0.408***
	(0.058)	(0.058)	(0.058)	(0.058)	(0.059)
Subs.600	0.696***	0.696***	0.695***	0.695***	0.703***
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
SQ	0.661***	0.709***	0.849***	0.899***	1.113***
	(0.059)	(0.067)	(0.068)	(0.075)	(0.079)
SQ×Thresh.25%		-0.112*		-0.109*	0.169**
		(0.057)		(0.057)	(0.074)
SQ×Thresh.25%		-0.0388		-0.0480	-0.184***
		(0.056)		(0.056)	(0.062)
SQ×Cocktail			-0.249***	-0.248***	-0.256***
			(0.055)	(0.055)	(0.056)
SQ×Testimony			-0.325***	-0.324***	-0.287***
			(0.061)	(0.061)	(0.062)
SQ×Thresh.25%×Belief					-1.042***
					(0.086)
SQ×Thresh.50%×Belief					-0.941***
					(0.098)
SQ×Thresh.75%×Belief					-1.257***
					(0.179)
N	22896	22896	22896	22896	22896
ll	-7146.9	-7144.9	-7130.1	-7128.3	-6975.2

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.5 Robustness check

Table A.5: Mixed logit estimations without subsidy.

	(1)	(2)	(3)	(4)
Mean				
Information	-0.141**	-0.140**	-0.145**	-0.141**
	(0.071)	(0.071)	(0.071)	(0.071)
Alert	1.394***	1.394***	1.385***	1.393***
	(0.068)	(0.068)	(0.066)	(0.067)
Confidentiality	1.093***	1.093***	1.086***	1.086***
	(0.081)	(0.081)	(0.080)	(0.080)
Price (in k€)	-1.557***	-1.557***	-1.549***	-1.554***
	(0.065)	(0.065)	(0.064)	(0.065)
SQ	-0.0264	0.0933	0.495***	0.248*
	(0.100)	(0.149)	(0.152)	(0.150)
SQ×Thresh.25%		-0.204	0.239	
		(0.198)	(0.198)	
SQ×Thresh.75%		-0.159	-0.437**	
		(0.193)	(0.189)	
SQ×Belief			-1.819***	
			(0.206)	
SQ×Cocktail				-0.391**
				(0.185)
SQ×Testimony				-0.442**
				(0.211)
SD				
Information	1.283***	1.282***	1.279***	1.265***
	(0.106)	(0.106)	(0.102)	(0.105)
Alert	1.040***	1.042***	1.001***	1.034***
	(0.094)	(0.094)	(0.094)	(0.094)
Confidentiality	1.486***	1.489***	1.469***	1.494***
	(0.103)	(0.103)	(0.101)	(0.103)
SQ	2.336***	2.332***	2.194***	2.293***
	(0.101)	(0.102)	(0.108)	(0.111)
SQ×Thresh.25%		0.166	-0.415	
		(0.493)	(0.529)	
SQ×Thresh.75%		-0.00566	0.0725	
		(0.378)	(0.400)	
SQ×Belief			-0.476	
			(0.481)	
SQ×Cocktail				0.0825
				(0.313)
SQ×Testimony				0.826
				(0.581)
Number of obs.	22896	22896	22896	22896
Log-likelihood	-6039.2	-6038.5	-5995.4	-6035.7

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Mixed logit estimations with Price less subsidy variable.

	(1)	(2)	(3)	(4)
Mean				
Information	-0.0585	-0.0580	-0.0666	-0.0571
	(0.074)	(0.074)	(0.074)	(0.074)
Alert	1.687***	1.688***	1.676***	1.686***
	(0.076)	(0.076)	(0.074)	(0.075)
Confidentiality	1.287***	1.288***	1.275***	1.280***
	(0.087)	(0.087)	(0.086)	(0.087)
Net price (in k€)	-1.644***	-1.644***	-1.633***	-1.639***
	(0.061)	(0.061)	(0.061)	(0.061)
SQ	0.568***	0.689***	1.103***	0.852***
	(0.095)	(0.150)	(0.153)	(0.150)
SQ×Thresh.25%		-0.203	0.243	
		(0.206)	(0.205)	
SQ×Thresh.75%		-0.163	-0.456**	
		(0.202)	(0.196)	
SQ×Belief			-1.871***	
			(0.213)	
SQ×Cocktail				-0.404**
				(0.193)
SQ×Testimony				-0.474**
				(0.220)
SD				
Information	1.337***	1.336***	1.331***	1.313***
	(0.113)	(0.112)	(0.108)	(0.111)
Alert	1.166***	1.168***	1.124***	1.155***
	(0.097)	(0.097)	(0.097)	(0.097)
Confidentiality	1.588***	1.592***	1.569***	1.595***
	(0.108)	(0.109)	(0.105)	(0.108)
SQ	2.427***	2.423***	2.285***	2.385***
	(0.107)	(0.108)	(0.115)	(0.119)
SQ×Thresh.25%		0.178	-0.483	
		(0.493)	(0.525)	
SQ×Thresh.75%		0.00455	0.101	
		(0.409)	(0.422)	
SQ×Belief			-0.462	
			(0.494)	
SQ×Cocktail				0.0806
				(0.344)
SQ×Testimony				0.873
				(0.662)
Number of obs.	22896	22896	22896	22896
Log-likelihood	-5883.9	-5883.3	-5841.1	-5880.6

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$